Brain–Computer Interface Contributions to Neuroergonomics

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Abstract

Brain-Computer Interfaces (BCIs) are systems that can translate brain activity patterns into messages or commands for an interactive application. As such the technology used to design them, and in particular to design passive BCIs which are a new means to perform mental state monitoring, can greatly benefit the neuroergonomics field. Therefore, this chapter describes the classical structure of the brain signal processing chain employed in BCIs, notably presenting the typically used preprocessing (spatial and spectral filtering, artefact removal), feature extraction and classification algorithms. It also gives examples of the use of BCI technology for neuroergonomics applications, either offline for evaluation purposes (e.g. cockpit design or stereoscopic displays' assessment), or online for adaptation purposes (e.g. video game difficulty level or air traffic controller display adaptation).

Keywords: Brain-Computer Interface, Neuroergonomics, EEG

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1. Introduction

Brain-Computer Interfaces (BCIs) are communication and control systems that enable their users to send commands and messages to a computer application by using only their brain activity, this activity being measured and processed by the system (Clerc et al., 2016a). A typical example of a BCI would be an application in which the user can move a cursor on a computer screen towards the left or towards the right, by imagining left or right hand movements respectively. While there are various ways to measure brain activity in BCIs (Wolpaw et al., 2006), portable brain imaging techniques are typically used for practical applications. In particular, ElectroEncephaloGraphy (EEG) and functional Near InfraRed Spectroscopy (fNIRS) have been used for practical BCI applications, outside laboratories. Nonetheless, EEG remains by far the most used measure of brain activity for BCI design, both in laboratories and in real-life applications. Therefore, in the rest of this chapter, we are going to focus only on EEG-based BCIs.

BCIs can be divided into 3 categories: active, reactive and passive BCIs (Zander & Kothe, 2011). With an **active BCI**, the user voluntarily imagines some specific mental tasks (e.g., imagining left or right hand movements), whose resulting EEG patterns are translated into specific commands, e.g., moving the cursor left when the BCI recognizes an imagine left hand movement in EEG signals.

With **reactive BCIs**, various stimuli (often visual ones) are presented to the user, each one associated to a different command. Each stimulus is designed to evoke a different brain response (Event Related Potential - ERP - or Evoked Response EP) when the user pays attention to it. This brain response can be detected in EEG signals and thus translated into the command associated to this stimulus. The most iconic example of reactive BCIs is the P300-speller, in which the user is presented with a matrix containing all letters of the alphabet, these letters being randomly flashing (Clerc et al., 2016b). The user is asked to pay attention to flashes on the letter he wants to spell (the target letter), which will give rise to a P300 ERP (a positive increase in EEG signal amplitude appearing about 300 ms after a rare and relevant stimulus) in the user's EEG signals when the target letter is flashed. No such P300 will appear when other letters are flashed. This thus enables to identify the target letter by finding out which letter evokes a P300 when flashed.

Another very widespread type of reactive BCIs are Steady-State Visual Evoked Potential (SSVEP)-based BCIs. With such BCIs, the user is presented with various flickering visual objects (e.g., buttons on screen), each object flickering at a different frequency and being associated to a different command. If the user pays attention to one of these flickering objects, it will give rise to an SSVEP in his/her EEG signals, i.e., in an increase of occipital EEG signal power at the same frequency as the flickering frequency of the object, and at its harmonics. For instance, paying attention to a button flickering at 10Hz, would lead to an increase in 10 Hz EEG power, and possibly 20 Hz EEG power as well. Detecting the SSVEP enables to identify the object the user is paying attention to, and thus to send the corresponding command.

Finally, **passive BCIs** are used to monitor the user's mental states in order to adapt the application accordingly, without the user sending any volontary command through EEG signals. For instance, a passive BCI can be used to continuously estimate mental workload levels in EEG signals in order to present the user with a human-computer interface, e.g., a plane cockpit interface, that is not too cognitively difficult too use, nor too boring.

Passive BCIs are typically the kind of BCIs that can be used for neuroergonomics research and applications. Nonetheless, many of the tools developed for active and reactive BCI, and in particular EEG signal processing tools, are the same as the ones used for passive BCIs, and thus that can be used for neuroergonomics as well. Therefore, in this chapter, we present a short overview of the tools developed for BCI research that can contribute to neuroergonomics. In particular, we will first briefly present tools to process and classify EEG signals online, in order to estimate the user mental state. Then we will show how passive EEG-based BCIs can be used for neuroergonomics and illustrate this with existing works. We then present some brief perspectives for the field.

2. Signal Processing

In BCI research, various signal processing tools were developed to estimate in real-time the users' mental states from their EEG signals, and this despite the noisy, non-stationary and data scarce nature of those signals. Typically, EEG signal processing in BCI follows a pattern recognition pipeline, which consists in:

1. Preprocessing EEG signals, which mostly consists in filtering them to increase their Signal-to-Noise Ratio (SNR);
2. Extracting features to describe EEG data in a compact way;
3. Classifying these features (Lotte et al., 2007; Bashashati et al., 2007; Makeig et al., 2012).

We describe below the main approaches available to perform these different steps, with a focus on approaches that can be used online. In addition, all these steps can be dynamically adapted online as well, so we briefly mention how this can be done.

2.1. Preprocessing

Preprocessing EEG signals typically consists in filtering the signal in various ways, in order to reduce the influence of artefacts such eye movements (ElectroOculoGraphy - EOG) or muscle tension (ElectroMyoGraphy - EMG) (Fatourechi et al., 2007), and to highlight the EEG patterns representative of the mental state of interest. The most basic filtering is spectral filtering, i.e., restricting the EEG signals to some specific oscillatory components, e.g., only the alpha (8-12 Hz) and theta (4-7 Hz) rhythms to estimate mental workload. Interestingly enough, some algorithms were developed to automatically identify the best frequency band for each subject, see, e.g., (Pregenzer & Pfurtscheller, 1999).

Another essential preprocessing step is spatial filtering, i.e., combining the signals from multiple EEG channels in order to obtain a new signal with higher SNR. Different algorithms were developed to optimize spatial filters from examples of EEG data, in order to obtain EEG features that are maximally different between mental states, so as to recognize them as well as possible (Blankertz et al., 2008). For online applications, we can notably cite the Common Spatial Patterns (CSP) algorithm to estimate mental states based on oscillatory activity (Blankertz et al., 2008), or xDAWN to estimate states based on Event Related Potentials (Rivet et al., 2009; Roy et al., 2015). The Source Power COmodulation (SPOC) algorithm also enables to find spatial filters such that the power of the spatially filtered signals maximally co-vary with a continuous target variable (Dähne et al., 2014). As such it can be used to estimate continuous mental states, such as attention or workload levels. Some extensions of such algorithms were also proposed so as to be more robust to noise or limited training data (Samek et al., 2014; Lotte, 2015).

Finally, reducing the influence of EOG or EMG artefacts is also desirable. While there are many effective algorithms to remove artefacts offline based on Independent Component Analysis (ICA) (Urigüen & Garcia-Zapirain, 2015), these algorithms typically cannot be used online as they are not computationally efficient enough. For online application, simpler and faster, but nonetheless useful algorithms are used. Notably, to remove EOG, regression-based algorithms based on explicit measures of EOG are often used (Schlögl et al., 2007). For removing more general types of artefacts online, an interesting recent development is the FORCe algorithm, which combines wavelet decompositions and heuristics to remove artefactual wavelet components (Daly et al., 2015).

2.2. Feature extraction

Once the EEG processed, they can be described by features (Bashashati et al., 2007). For BCIs based on oscillatory activity, the typically extracted feature are the Band Power (BP) of the EEG signals in various frequency bands and channels. For ERP-based BCIs, the used features are typically the amplitude of the preprocessed EEG time points, for each channel, after down-sampling (Blankertz et al., 2010). These two types of features are by far the most used and give good results. It should be mentioned though that other types of features are being explored, such as complexity features, describing signal regularities, or connectivity features, quantifying how synchronized signals from different channels or frequency bands are (Lotte, 2014). While these are not as efficient as BP or time points, they can improve the overall accuracy when used in combination with them.

2.3. Classification

Classifiers learn from data which feature values correspond to which class, i.e., to which mental state here. There are multiple variants of classifiers that have been explored for BCIs, see (Lotte et al., 2007) for a review. When it comes to online use though, only a few classifiers are typically used, the main ones being Linear Discriminant Analysis (LDA) (and its variants such as shrinkage LDA (Blankertz et al., 2010) or Step-wise LDA (Lotte et al., 2007)) and Support Vector Machine (SVM). Both classifiers are linear, and are fast to train and to use. They can also be trained from rather little training data, which makes them ideal for practical online BCI use. In recent developments, Riemannian geometry-based classifiers, which classify covariance matrices rather than vector of features, also prove very promising, including online (Yger et al., 2017; Barachant et al., 2012).

2.4. Adaptation

As previously mentioned, EEG signals tend to be non-stationary, and the environment in which the BCI is used also leads to varying amount of external noise. As such, to reach optimal performances, it is worth considering adaptive signal processing algorithms, whose parameters are dynamically changed and optimized during online use (Shenoy et al., 2006). There are a number of variants of the above mentioned algorithms that were thus designed so as to optimize online, in an incremental way, the spectral filters, spatial filters, features and classifiers, as new EEG data become available (see (Mladenovic et al., 2017, in press) for a review). While most of these algorithms remain to be tested in ecological conditions outside laboratories, they seem promising to deal with EEG fluctuations due to variation in context, noise and recording conditions that are typically encountered in real-life applications.

3. Contributions to Neuroergonomics

As explained earlier, since the beginning of the twentieth century the Brain-Computer Interface technology has been transposed to monitoring mental states of users. Systems that take into account information about mental states extracted from neurophysiological measures have been called biocybernetic systems or passive BCIs (Fairclough, 2009; Zander & Kothe, 2011; Roy & Frey, 2016). Such systems can be used either offline or online, with different applicative goals and for various mental states. Definitions of mental states critical for the neuroergonomics field are given below, as well as examples of applications.

3.1. Mental states

There is a diversity of mental states that are relevant for characterizing a user/operator's state. The mental states of interest can be separated into two categories, the mental states linked to the main characteristics of the task performed by the user/operator, e.g., fatigue, and mental states linked to critical states of the system the operator interacts with, e.g., inattentional blindness. Those two types of mental states globally generalize to the level to which the subject/operator has recruited and engaged cognitivo-attentional resources. Therefore, one can consider that the mental states linked to the main characteristics of the task relate to **global** resource engagement, while mental states linked to critical states of the system relate to **local** resource engagement. Examples of mental states that fall into these categories and that are classically estimated in neuroergonomics applications are listed in Table 1 below. For more details on each of these mental states please refer to (Roy & Frey, 2016).

It is worth noting that in addition to the mental states listed above which mainly rely on cognitive processes, emotional/affective states are of tremendous importance, as they are inseparable from cognitive states. For instance, workload can induce stress and frustration. It is therefore important to realize that mental states are never measured separately, which may be why systems trained on a particular set of data acquired in a specific setting are generally difficult

Table 1: Mental states classically estimated in neuroergonomics applications and generated in response to either main characteristics of the task or critical states of the system.

Main characteristics of the task	Linked to **time-on-task**: fatigue, vigilance, boredom and mind wandering; Linked to mental **workload**: load in working memory, divided attention, social or temporal stress.
Critical states of the system	Inattentional blindness or deafness phenomena, automation surprise/confusion.

to apply on another set acquired in a different setting. What's more, all these mental states interact in real life settings and thus decrease the system's performance if the latter is not conceived accordingly (Roy et al., 2013). For a review on affective BCIs please refer to (Mühl et al., 2014).

3.2. Offline use: Evaluation

Passive BCIs technologies can be used offline, and in fact to this day they mostly are. More particularly, they are used for different purposes, the primary one being the **evaluation of a product**, a work setting or a work task, in order to determine their usability, performance, and generally their impact on the user. Hence, passive BCIs can be used for the evaluation of the comfort of stereoscopic displays (Frey et al., 2016), for the evaluation of the difficulty of a game (Allison & Polich, 2008), a multitasking environment (Roy et al., 2016), a flying task (Dehais et al., 2016) or a surgical training procedure (Zander et al., 2016), and also for the evaluation of prolonged and monotonous tasks such as driving (Yeo et al., 2009). Another way of using these systems is to perform an **evaluation of the user** him/herself, for instance to determine his/her fitness to perform a coming task, or to determine his/her learning type. This could be promising, and to our knowledge has not been done yet.

3.3. Online use: Adaptation

Passive BCIs aim at being used online, and ideally should be so. Although to this day the scientific literature on the subject is mostly speculative, it seems to be the goal of most researchers in the field. The online use of passive BCIs allows to "close the loop" between a user and the system, and also to include the user in a more global system and regard him/her as a sub-system herself. In order to do so the system has to adapt to the measured and inferred mental states of the user using counter-measures -if the detected state has a negative impact on performance- or more generally implicit modifications of the system. Most studies developed and presented in the offline use section actually intend to progress towards an online evaluation of the user's mental states.

Since a few years the technological developments and the increase in variety of origin of the community members have allowed the implementation of systems that perform the measurements online, with for instance using fNIRS an online in-flight workload monitoring (Gateau et al., 2015), and using EEG during classical human-computer interaction tasks (Heger et al., 2010) and numerical learning tasks (Spüler et al., 2016).

Also, a few studies have recently been published with an actual **adaptation** of the system to the user's mental state as inferred from neurophysiological measures. For instance, workload level detection through EEG can be used to adapt the level of difficulty of a multitasking environment (i.e. the Multi-Attribute Task Battery) (Prinzel et al., 2000) and more recently that of a Tetris video game (Ewing et al., 2016) and of an air-traffic controller display (Aricò et al., 2016). Additionally, passive BCIs can also be used to improve active BCIs, i.e., in which the user controls an effector. This was demonstrated by Chavarriaga and collaborators who used the EEG responses to errors committed by the active BCI (a.k.a., Error Related Potentials) to adapt the whole system and increase its performance (Chavarriaga & del R Millán, 2010).

4. Perspectives

Passive brain-computer interfaces offer a very promising means to achieve online objective mental state monitoring of users and operators. Therefore it is of great interest to pursue their development for neuroergonomics applications. Even though the literature on passive BCIs has increased drastically these last few years most research is still conducted in laboratory and not in ecological settings. Yet portable recording devices that are quite robust to environmental noise have been released (e.g. dry EEG systems (Nijboer et al., 2015)). Therefore, this may be due to the lack of neural features and learning algorithms robust to changes in tasks, settings and subjects. Research should therefore focus on these matters, as well as try and develop systems that actually work online but also adapt both at the signal processing level and at the interface level.

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